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Higher Rates Of Homelessness Are Associated With Increases In Mortality From Accidental Drug And Alcohol Poisonings

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ABSTRACT Alcohol and drug overdoses have multiple complex causes. In this article we contribute to the literature that links homelessness, the most extreme form of housing disruption, to accidental SUD-related poisonings. Using plausibly exogenous variation from a state's landlord-tenant policies that influence evictions, we estimated the causal impact of homelessness on SUD-related mortality. We found large effects of homelessness on SUD-related poisonings (for example, a 10 percent increase in homelessness led to a 3.2 percent increase in opioid poisonings in metropolitan areas). Our findings indicate that reducing local homelessness rates from the seventy-fifth to the fiftieth percentile levels could have saved more than 1,900 lives from opioid overdoses across all metropolitan localities in the final year of our study data. We conclude that strengthening the social safety net in terms of housing security could help curb the ongoing SUD-related poisoning epidemic in the US.

Housing instability is a persistent problem in the US. Evictions declined from 1,019,600 in 2006 to 898,479 in 2016.¹ Homelessness rates are also high. There is a modest literature on the impact of public policies on eviction and adverse health outcomes.^{1,2} As those papers note, eviction usually results in subsequent substandard housing and is inherently stressful. This existing literature has demonstrated a link between eviction and substance use disorder (SUD)-related mortality. In this article we examine the final and most severe step in the process of housing instability by investigating the relationship between homelessness and SUD-related mortality. Taken together, these studies map how the steps of eviction and homelessness are associated with accidental SUD-related poisonings. Homelessness is arguably more disruptive than eviction, and newly homeless people are pushed into populations with high rates of risky behaviors. Ex ante, local-

ities with high eviction rates and high levels of homelessness should be expected to have higher rates of SUD-related mortality than areas with high levels of eviction but low rates of homelessness. However, this hypothesis has yet to be tested in the literature.

During the COVID-19 pandemic, widespread moratoria on evictions were imposed, first by some states and localities and then nationally by the Centers for Disease Control and Prevention (CDC).³ The federal moratorium expired in 2021, leading many to expect a wave of evictions as stalled cases began to move through the courts.⁴ The first evidence of this appeared by mid-2023, as the number of evictions rose, exacerbated by a surge in rent and housing prices.^{3,5} A rapid surge in evictions could translate into sharply increased rates of homelessness over already persistently high rates. This article assesses how changes in the rate of homelessness affected accidental SUD-related poisonings.

For more than a decade, the US has suffered a

mortality crisis stemming from opioid and other substance misuse.⁶ Drug overdose deaths involving prescription opioids more than quadrupled between 1999 and 2019.⁷ These trends have been found to be worse in parts of the US with higher rates of poverty and unemployment.⁸ The number of opioid prescriptions filled peaked in 2012 (at the end of what is known as the “first wave” of the epidemic), and opioid prescribing has fallen steadily since,⁹ although the number of days supplied and the number of prescriptions with more than a thirty-day supply continued to rise for some time.¹⁰ With the steady decline in opioid prescriptions, the epidemic had a “second wave” driven primarily by heroin mortality, before moving into an even deadlier “third wave” of fentanyl-associated deaths.¹¹ Opioid mortality has received most of the media and research attention of late, yet poisonings from other substances, including cocaine, benzodiazepines, and alcohol, remain high.^{12–14}

As early as the 1990s, the prevalence of alcohol or drug use disorders was observed to be very high among people who were homeless, with reported rates of drug misuse as high as 40 percent, as reported in an article published in 1991.¹⁵ One small-area study, published in 2018, suggested that SUD-related overdose was also a leading cause of death among the homeless population during 2009–09, with opioid poisoning accounting for 29 percent of their overdose deaths.¹⁶ Another small-scale study, published in 2016, of a group of people who were homeless who died from opioid poisoning during 2003–08 was able to document opioid use disorders in about 54 percent of people examined.¹⁷ More recently, locality-specific cohort studies have found a more than proportional prevalence of SUD mortality among people experiencing homelessness.^{18–21} Nevertheless, there is a relative paucity of evidence about the relationship between homelessness and SUD-related deaths—particularly evidence that addresses statistical simultaneity across the two phenomena.

Although there is evidence that SUD and homelessness are highly correlated, the direction of this relationship remains unclear, as most of the evidence presents associations or is inconclusive.^{22–24} Social selection and social adaptation models have been used to explain drug disorders as both cause and consequence of homelessness.²⁵ It is plausible that the direction of causality might run in both directions, with some people developing SUDs before eviction and homelessness and others developing disorders after both eviction and homelessness, in part of a chain of events in which poverty or mental health issues strike and substance use provides a coping mechanism.^{26,27}

In this study, we focused on the path that starts from homelessness and leads to SUD-related poisoning mortality without taking a position regarding whether underlying SUD precedes or is caused by homelessness. We exploited plausible exogenous variation in changes in housing policy that affected the number of people who were homeless in a locality and allowed us to explore the causal effect in one direction: from homelessness to SUD-related mortality. We extend the previous literature by examining national data (not just a single community) and by estimating plausibly causal models (exploiting variation in housing policies) of the link between homelessness and SUD-related mortality.

Study Data And Methods

DATA Data for this study span 2007–17 (years in which homelessness data are available from the Department of Housing and Urban Development [HUD]). Online appendix A1.1 provides details on variable construction.²⁸ Our dependent variables were the rates of accidental poisoning for nine categories of substances tracked by the CDC: overall opioid use, prescription opioids, synthetic opioids (such as fentanyl), heroin, cocaine, stimulants, benzodiazepines, antidepressants, and alcohol. We only captured accidental alcohol poisonings and, following prior studies, did not include other alcohol-related deaths, such as liver disease and cancer. In appendix exhibit 3 we present average mortality rates for each of the tracked substances.²⁸

Our key independent variables were local homelessness rates, where “local” refers to HUD-defined Continuum of Care areas.²⁹ These areas are geographically defined by individual counties, multiple contiguous counties, or, less frequently, metropolitan areas. HUD divides almost the entire country into approximately 375 Continuum of Care localities. HUD requires that these areas conduct a census of the homeless population in their geographic areas each year on the same night in January; the areas count all sheltered and unsheltered people in their regions to generate what are known as point-in-time estimates of the homeless population. We extracted six measures of homelessness from the point-in-time data: all homeless people, sheltered homeless people, unsheltered homeless people, people who were chronically homeless, sheltered chronically homeless people, and unsheltered chronically homeless people. “Sheltered” means that a person was in a homeless shelter, domestic violence shelter, or a hotel or motel where HUD paid for the stay; “unsheltered” means that the person was found not living in a permanent structure. HUD defines

chronic homelessness as a situation in which a person is homeless for one continuous year or has had four or more episodes of homelessness in the past three years.³⁰

As the relationship between homelessness and SUD incidence might go in both directions, we used several instrumental variables that predicted homelessness (through eviction) and that arguably did not affect SUD mortality: various state landlord-tenant laws shown to predict evictions³⁰ and HUD housing support variables. In two recent papers,^{1,2} researchers extracted a set of policy indicator variables capturing state laws regulating landlord-tenant relationships, using editions of *Every Landlord's Legal Guide* and *Every Tenant's Legal Guide* from 2000 through 2018.^{31,32} The authors used the appendix tables in each year's guides to code indicator variables for the following state policies: prohibitions against eviction filings in small claims court, prohibitions against landlord retaliation for tenant actions, and whether there is a mandated waiting time for lease violations before an eviction pleading can be filed. We took the policy variables from tables provided in the publications cited above.

These variables have been shown to correlate with local eviction rates,^{1,2} but they can be excluded from the main equation of interest because they are not directly predictive of substance-related mortality rates. Appendix section A1.3 explains how we tested the performance of these instrumental variables.²⁸

Finally, sociodemographic control variables were collected from the Area Health Resources File and aggregated at the Continuum of Care area level. The summary statistics for these variables are in appendix exhibit 3.²⁸

METHODS We first illustrated the relationship between homelessness and SUD mortality in each individual state. Because many of the non-homelessness covariates we included in our models were important for differentiating mortality across different states, we ran a version of the overall opioid mortality model including all variables except homelessness (and the first-stage residual). The residual from this series reflected any-opioid mortality purged of the effects of the covariates but retaining the correlation with homelessness. Appendix exhibit 1 presents the residualized series of opioid mortality and the overall homelessness rate.²⁸ For most states and years, we found expected trends between homelessness and mortality, thus providing preliminary support for the associations we sought to estimate causally.

We next employed two-stage residual inclusion regressions to implement the instrumental variables models and explore the degree to which homelessness was associated with SUD mortality.

Increases in homelessness triggered by the end of the pandemic should ultimately be accompanied by increased numbers in SUD mortality.

Appendix A1.2 offers a thorough discussion about the estimation and estimates of the first-stage partial F statistics (appendix exhibit 5), their respective coefficients (appendix exhibit 6), and *p* values in the second stage from the first-stage residuals as a test for exogeneity (appendix exhibit 7).²⁸

Our identification strategy relied on the plausibly exogenous variation in the introduction and implementation of varying landlord-tenant housing policies by state governments relative to SUD mortality. Variation from these policies accounts for the simultaneity of the relationship between homelessness and SUD-related mortality and opens a path from tightening housing regulation to homelessness, and only then affects SUD-related mortality.

There was ambiguity about which months to include when we measured SUD-related mortality. The point-in-time homelessness censuses are always conducted on a single night in January, suggesting that we count deaths that are proximate to that date (for example, from January through March); however, shortening the time frame for including deaths could decrease the signal-to-noise ratio, as SUD-related deaths are still relatively rare. We opted to count mortality for the first quarter of each given year.

Some concerns might remain about omitted variable bias if states choose policies based in part on latent factors (for example, states with weak tenant protections may also have weak social safety nets that affect homelessness and SUD-related poisonings together). We tested the effectiveness of our two-stage residual inclusion method in eliminating meaningful endogeneity bias, using a procedure to assess coefficient stability and remaining influence from observables developed by Emily Oster.³³ Details of this

test are in appendix A1.3.²⁸ Evidence suggested that our two-stage residual inclusion method worked well to eliminate substantive likelihood of endogeneity bias for most of our exercises. We concluded that our instruments, which were theoretically justified, were also empirically strong.

Our main results are presented as transformations of the coefficients obtained from equation [4] from appendix A1.2.²⁸ We converted the coefficients into measures of responsiveness (technically known as “elasticities”), which reflect what percentage change in mortality is associated with a 1 percent change in the measure of homelessness used in each model. There are two broad types of Continuum of Care areas: compact geographies of one or only a few counties mostly centered on metropolitan areas, and large, diverse geographies generally constituting “rest of state” areas. The latter group is extremely heterogeneous geographically and often contains large (low-populated) areas of each state. We excluded the latter group and focused our analysis on more geographically compact urbanized Continuum of Care areas.

LIMITATIONS Our model had several limitations. First, given that the point-in-time homelessness census takes place over the course of one night in January nationwide, the homeless counts in the data may have misrepresented the actual average homelessness levels in each Continuum of Care area over the year. Second, some Continuum of Care areas are geographically diverse “rest of state” areas, where the homeless counts may be less accurate. We addressed these two limitations by focusing on metropolitan localities (where the point-in-time counts are likely to be more reliable) and estimating versions of

the models using only first-quarter mortality; we assessed robustness by also estimating models with annual mortality as sensitivity tests. If the point-in-time count of the homeless population during January is an undercount of homeless people, our estimates may represent a lower-bound effect. Third, the consistency of the two-stage residual inclusion depended on the validity of our exclusion restrictions and the strength of the instruments we selected. Our coefficient stability tests provided reassurance that any remaining endogeneity bias was ignorable, but the usual caveats about instrumental variables methods still apply.

Study Results

TWO-STAGE RESIDUAL INCLUSION Exhibits 1 and 2 present the estimated effects of the different measures of homelessness on opioid-related and non-opioid-related SUD mortality (respectively). The highest elasticities were found in the models for synthetic opioids, cocaine, and alcohol, where the elasticities for increases in the overall homelessness rate were greater than 0.50. For example, we found that a 1 percent increase in the overall homelessness rate was associated with an approximately 0.5 percent increase in synthetic opioid deaths. Across all measures, the estimated elasticities of homelessness on alcohol mortality were generally the largest, ranging from 0.368 to 0.557. The estimated elasticities for the various homelessness measures were also relatively large (and statistically significant) for synthetic opioids (for example, fentanyl) and cocaine.

With respect to the various measures of home-

EXHIBIT 1

Relative responsiveness of opioid-related mortality to homelessness rates, using January–March point-in-time data restricted to only metropolitan Continuum of Care areas, 2007–17

	Overall opioids	Prescription opioids	Synthetic opioids	Heroin
Overall homelessness rate	0.315***	0.289***	0.503***	0.392***
Sheltered homelessness rate	0.336***	0.297***	0.536***	0.396***
Unsheltered homelessness rate	0.194**	0.190***	0.306*	0.320***
Chronic homelessness rate	0.253***	0.252***	0.308**	0.295***
Sheltered chronic homelessness rate	0.271***	0.248***	0.398***	0.313***
Unsheltered chronic homelessness rate	0.210***	0.207***	0.276***	0.264***

SOURCE Authors’ calculation based on analysis of accidental substance use disorder (SUD)-related poisonings extracted from the Multiple Cause of Death Vital Statistics files. **NOTES** There were 2,651 Continuum of Care–year observations. Each row represents a separate model of mortality, using various measures of homelessness as the key indicator variables. Models of the rate of SUD-related deaths weighted per 100,000 population. The parameters reflect the percent change in SUD-related mortality rates given a 1 percent change in the homelessness measure. Parameters are from two-stage residual inclusion models assuming that the homelessness rate is endogenous and estimated on all Continuum of Care localities. Levels of statistical significance are calculated using bootstrapped standard errors. All models also included local demographics, substance policies, first-stage residuals, and year and Continuum of Care area fixed effects. Instruments are in appendix exhibit 4 (see note 28 in text). *p < 0.10 **p < 0.05 ***p < 0.01

EXHIBIT 2

Relative responsiveness of nonopioid substance-related mortality to homelessness rates, using January–March point-in-time data restricted to only metropolitan Continuum of Care areas, 2007–17

	Stimulants	Benzodiazepines	Cocaine	Alcohol poisoning
Overall homelessness rate	0.346**	0.394***	0.508***	0.557***
Sheltered homelessness rate	0.249*	0.374***	0.556***	0.547***
Unsheltered homelessness rate	0.365***	0.322**	0.291***	0.397***
Chronic homelessness rate	0.257**	0.308***	0.411***	0.443***
Sheltered chronic homelessness rate	0.211*	0.309***	0.467***	0.466***
Unsheltered chronic homelessness rate	0.247**	0.265***	0.327***	0.368***

SOURCE Authors' calculation based on analysis of accidental substance use disorder (SUD)-related poisonings extracted from the Multiple Cause of Death Vital Statistics files. **NOTES** There were 2,651 Continuum of Care-year observations. Each row represents a separate model of mortality, using various measures of homelessness as the key indicator variables. Models of the rate of SUD-related deaths weighted per 100,000 population. The parameters reflect the percent change in SUD-related death rates given a 1 percent change in the homelessness measure. Parameters are from two-stage residual inclusion models assuming that the homelessness rate is endogenous and estimated on all Continuum of Care localities. Levels of statistical significance are calculated using bootstrapped standard errors. All models also included local demographics, substance policies, first-stage residuals, and year and Continuum of Care area fixed effects. Instruments are in appendix exhibit 4 (see note 28 in text). * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

lessness, models including overall homelessness rates and sheltered homelessness rates generally exhibited the largest estimated elasticities; the models explaining stimulant mortality differed from this trend, in that the elasticity associated with the unsheltered homelessness rate was larger than the elasticity for the sheltered homelessness rate.

Almost every mortality model rendered significant results for the effect of different levels of homelessness on SUD-related mortality, with the notable exemption of the models for antidepressant mortality, which, as indicated by the p values from first-stage residual inclusion (appendix exhibit 7), was the only mortality model that was not well identified.²⁸ As a consequence, for the sake of brevity, we do not present those results in exhibit 2.

One potential validity threat to the main results from exhibits 1 and 2 arose from the fact that a handful of Continuum of Care areas changed their geographic makeup during our study period. We estimated results only using data from stable Continuum of Care areas (more than 90 percent of our sample). We also tested our models using measured full-year SUD-related mortality. Finally, we report the estimation using nonmetropolitan Continuum of Care areas to contrast the results we obtained from metropolitan Continuum of Care areas.

Results of these sensitivity analyses are presented graphically in appendix exhibit 2.²⁸ In each panel, all of the elasticities pertaining to each of the mortality models are presented as whisker plots for ease of comparison of how the different changes we evaluated affected estimations. We found the noisiest and most attenu-

ated results in nonmetropolitan Continuum of Care areas. Results for complete annual mortality and constant geographic Continuum of Care areas were very stable.

COEFFICIENT STABILITY TEST OF ENDOGENEITY

We implemented a test of coefficient stability to assess the degree of selection bias, to assess to what extent our instruments dealt with endogeneity. We compared the relative degree of selection with and without the two-stage residual inclusion correction. Appendix exhibit 12 presents the estimated distribution of the parameter that captured the remaining unobservable variables influence relative to included variables (which Oster calls the coefficient of relative selection)³³ from a model of all-opioid mortality that used the overall homelessness rate as the treatment variable.²⁸ (See appendix A1.3 for details.)²⁸

From this exercise, we concluded that the two-stage residual inclusion was successful in accounting for unobservable selection for our main model (in which the dependent variable, overall mortality, was mortality from any opioid and the main independent variable was the total homelessness rate).

In appendix exhibit 13, we present the results from the tests for influential unobservables for all of the combinations of mortality-homelessness measures.²⁸ In twenty cases, there was not much evidence of a selection issue to begin with, in either the “exogenous homelessness” or the two-stage residual inclusion models. Among those cases where selection issues remained a concern (thirty-four cases), the two-stage residual inclusion procedure corrected the selection problem (twenty-five of fifty-four combinations). In five combinations, the improvement

provided by the two-stage residual inclusion was not large, and in four combinations the correction worsened the coefficient stability. Taken as a whole, however, the evidence suggests that our method of using two-stage residual inclusion with a set of rental policies as instruments worked well at eliminating endogeneity bias.

ESTIMATES OF POPULATION-LEVEL IMPACTS To better frame our primary results, we estimated additional calculations of the SUD-related deaths (for all metropolitan Continuum of Care areas) implied by the magnitude of our elasticity estimates that would have been associated with increases in the homelessness rate. Exhibits 3 and 4 present parameters and results of this exercise for opioid-related and non-opioid-related mortality, respectively, using average values across all years of the study.

A 1 percent increase in the mean overall homelessness rate for metropolitan Continuum of Care areas was equivalent to 2.16 additional homeless people per 100,000 population per Continuum of Care area, or 4,550 additional homeless people nationally (for metropolitan Continuum of Care areas); a 1-standard-deviation increase in the homelessness rate was equivalent to 179.7 additional homeless people per 100,000 population per Continuum of Care area, or 378,453 additional homeless people nationally (for metropolitan Continuum of Care areas); and moving from the median to the seventy-fifth percentile in the homelessness rate was equivalent to 86.4 additional homeless people per

100,000 population per Continuum of Care area, or 241,771 additional homeless people nationally (for metropolitan Continuum of Care areas). Given our estimates, these changes would imply 68, 5,661, or 1,964 additional “all-opioid” deaths (in all metropolitan Continuum of Care areas for a full year) for a 1 percent change, 1-standard-deviation change, and change from median to seventy-fifth percentile of homelessness rates, respectively. For cocaine mortality, the corresponding changes in full-year mortality from a 1 percent change, 1-standard-deviation change, and movement from the median to the seventy-fifth percentile of homelessness rates would have been 28, 2,286, and 539 additional deaths, respectively. Finally, the estimated change in alcohol mortality for the corresponding full-year mortality from a 1 percent change, 1-standard-deviation change, and movement from the median to the seventy-fifth percentile of homelessness rates would have been 30, 2,521, and 842 additional deaths, respectively.

Discussion

In this study we investigated the relationship between homelessness and SUD-related mortality. This relationship has been understudied, despite the prevalence of SUD among the homeless population and the persistent seriousness of the opioid crisis.^{7,8} We used plausibly exogenous var-

EXHIBIT 3

Estimated average change in opioid-related mortality for metropolitan Continuum of Care area from increases in overall homelessness rates, 2007–17

	Overall opioids		Prescription opioids		Synthetic opioids		Heroin	
	Jan-Mar	Full year	Jan-Mar	Full year	Jan-Mar	Full year	Jan-Mar	Full year
Mortality								
Mean	17.0	68.1	8.8	34.1	4.3	18.3	5.2	22.0
Median	9	37	5	20	1	5	1	7
Overall homelessness rate								
Mean	216.0	216.0	216.0	216.0	216.0	216.0	216.0	216.0
Median	162.4	162.4	162.4	162.4	162.4	162.4	162.4	162.4
Standard deviation	179.7	179.7	179.7	179.7	179.7	179.7	179.7	179.7
75th percentile	248.8	248.8	248.8	248.8	248.8	248.8	248.8	248.8
Elasticity (from exhibit 1)	0.315	0.348	0.289	0.311	0.503	0.578	0.392	0.438
Change in national (metropolitan Continuum of Care area) opioid-related mortality from:								
1% change in mean homelessness rate	15.4	68.1	7.3	30.4	6.1	30.4	5.9	27.6
1 SD change in mean homelessness rate	1,277.1	5,661.0	609.7	2,531.8	510.8	2,530.9	491.0	2,298.1
Median to 75th percentile change in homelessness rate	432.4	1,963.8	220.4	948.7	76.7	440.8	59.8	467.6

SOURCE Authors’ calculation based on analysis of accidental substance use disorder (SUD)-related poisonings extracted from the Multiple Cause of Death Vital Statistics files. **NOTES** To calculate counterfactual lives saved in a changing opioid mortality environment, we used 2017 as the baseline for extrapolation. There were 287 metropolitan Continuum of Care areas in the US in 2017. The average number of homeless people counted during the point-in-time censuses was 454,952. The changes to the homelessness rate in the population would correspond to the following changes in the overall homeless population: 1 percent change: 4,550 additional homeless people; 1-standard-deviation change: 378,453 additional homeless people; and moving from the median to the 75th percentile Continuum of Care area for homelessness: 241,771 additional homeless people.

EXHIBIT 4

Estimated average change in cocaine- and alcohol-related mortality for metropolitan Continuum of Care areas from increases in overall homelessness rates, 2007–17

	Cocaine		Alcohol	
	Jan–Mar	Full year	Jan–Mar	Full year
Mortality				
Mean	4.6	19.0	4.9	19.1
Median	2	7	3	10
Overall homelessness rate				
Mean	216.0	216.0	216.0	216.0
Median	162.4	162.4	162.4	162.4
Standard deviation	179.7	179.7	179.7	179.7
75th percentile	248.8	248.8	248.8	248.8
Elasticity (from exhibit 2)	0.508	0.505	0.557	0.552
Change in national (metropolitan Continuum of Care area) cocaine- and alcohol-related mortality from:				
1% change in mean homelessness rate	6.7	27.5	7.8	30.3
1 SD change in mean homelessness rate	560.6	2,286.0	646.2	2,520.8
Median to 75th percentile change in homelessness rate	155.0	539.2	254.9	841.9

SOURCE Authors' calculation based on analysis of accidental substance use disorder (SUD)-related poisonings extracted from the Multiple Cause of Death Vital Statistics files. **NOTES** To calculate counterfactual lives saved in a changing opioid mortality environment, we used 2017 as the baseline for extrapolation. There were 287 metropolitan Continuum of Care areas in the US in 2017. The average number of homeless people counted during the point-in-time censuses was 454,952. The changes to the homelessness rate in the population would correspond to the following changes in the overall homeless population: 1 percent change: 4,550 additional homeless people; 1-standard-deviation change: 378,453 additional homeless people; moving from the median to the 75th percentile Continuum of Care area for homelessness: 241,771 additional homeless people.

iation from housing policy measures in instrumental variables models to identify the effect that homelessness had on SUD-related mortality rates.²

Among the different substances with potential for misuse, we focused on SUD-related mortality associated with opioids (prescribed, synthetic, and heroin), cocaine, antidepressants, stimulants, benzodiazepines, and alcohol. We also estimated our models using different definitions of homelessness rates, including overall homelessness, sheltered and unsheltered homeless people, and people who were chronically homeless.

For our benchmark exercise, the effect of a 1 percent change in the overall homelessness rate induced by housing policies was associated with a positive elasticity of 0.315 in the overall opioid mortality rate when estimated using data on metropolitan Continuum of Care areas. The largest elasticities were found in the models of synthetic opioids, cocaine, and alcohol, where the elasticities were all above 0.50. Most of the measures rendered statistically significant results across most of the mortality models we analyzed. In contrast, earlier research on evictions and SUD mortality found statistically significant elasticities of eviction on overall opioid mortality in the range of 0.127–0.183 and only

found statistically significant elasticities approaching 0.50 for synthetic opioids and heroin.²

Our findings have important policy implications. Although homelessness is associated with substance-related policies, our first-stage models indicated that several landlord-tenant policies may be effective at mitigating homelessness. This should lead to a renewed interest in understanding the mechanisms through which such policies induce homelessness and SUD among the homeless population. Although opioids have received most of the recent media and research attention, mortality from the misuse of other substances, both legal and illegal, was also affected by changes in homelessness. Increased attention to how housing instability and other social disruptions from nonopioid substances is also warranted. In the light of the aftermath of the COVID-19 eviction moratorium, our models predict that increases in homelessness triggered by the end of the moratorium should ultimately be accompanied by increased numbers in SUD mortality.

For continuing research, a better understanding of the causal mechanisms through which housing and other policies affect poisoning mortality still needs to be developed. ■

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NOTES

- 1 Bradford AC, Bradford WD. The effect of state and local housing policies on county-level rent and evictions in the United States, 2004–2016. *Hous Policy Debate*. 2023 Nov 7. [Epub ahead of print].
- 2 Bradford AC, Bradford WD. The effect of evictions on accidental drug and alcohol mortality. *Health Serv Res*. 2020;55(1):9–17.
- 3 Vallejo C, Haas J, Hepburn P. Preliminary analysis: eviction filing patterns in 2022 [Internet]. Princeton (NJ): Princeton University, Eviction Lab; 2023 Mar 9 [cited 2023 Nov 30]. Available from: <https://evictionlab.org/ets-report-2022/>
- 4 Liptak A, Thrush G. Supreme Court ends Biden's eviction moratorium. *New York Times* [serial on the Internet]. 2021 Aug 26 [last updated 2021 Nov 7; cited 2023 Dec 22]. Available from: <https://www.nytimes.com/2021/08/26/us/eviction-moratorium-ends.html>
- 5 Duca JV, Murphy A. Why house prices surged as the COVID-19 pandemic took hold [Internet]. Dallas (TX): Federal Reserve Bank of Dallas; 2021 Dec 28 [cited 2023 Nov 30]. Available from: <https://www.dallasfed.org/research/economics/2021/1228>
- 6 Salam M. The opioid epidemic: a crisis years in the making. *New York Times* [serial on the Internet]. 2017 Nov 26 [cited 2023 Nov 30]. Available from: <https://www.nytimes.com/2017/10/26/us/opioid-crisis-public-health-emergency.html>
- 7 National Institute on Drug Abuse. Drug overdose death rates [Internet]. North Bethesda (MD): NIDA; 2023 Jun 30 [cited 2023 Nov 30]. Available from: <https://nida.nih.gov/research-topics/trends-statistics/overdose-death-rates>
- 8 Spiller H, Lorenz DJ, Bailey EJ, Dart RC. Epidemiological trends in abuse and misuse of prescription opioids. *J Addict Dis*. 2009;28(2):130–6.
- 9 Centers for Disease Control and Prevention. Drug overdose, US dispensing rate maps [Internet]. Atlanta (GA): CDC; [cited 2023 Nov 30]. Available from: <https://www.cdc.gov/drugoverdose/txrate-maps/index.html>
- 10 Guy GP Jr, Zhang K, Bohm MK, Losby J, Lewis B, Young R, et al. Vital signs: changes in opioid prescribing in the United States, 2006–2015. *MMWR Morb Mortal Wkly Rep*. 2017;66(26):697–704.
- 11 Ciccarone D. The triple wave epidemic: supply and demand drivers of the US opioid overdose crisis. *Int J Drug Policy*. 2019;71:183–8.
- 12 Kleinman RA, Weiss RD. Benzodiazepine-involved overdose deaths in the USA: 2000–2019. *J Gen Intern Med*. 2022;37(8):2103–9.
- 13 Tori ME, Larochelle MR, Naimi TS. Alcohol or benzodiazepine co-involvement with opioid overdose deaths in the United States, 1999–2017. *JAMA Netw Open*. 2020;3(4):e202361.
- 14 White AM, Castle IP, Hingson RW, Powell PA. Using death certificates to explore changes in alcohol related mortality in the United States, 1999 to 2017. *Alcohol Clin Exp Res*. 2020;44(1):178–87.
- 15 McCarty D, Argeriou M, Huebner RB, Lubran B. Alcoholism, drug abuse, and the homeless. *Am Psychol*. 1991;46(11):1139–48.
- 16 Roncarati JS, Baggett TP, O'Connell JJ, Hwang SW, Cook EF, Krieger N, et al. Mortality among unsheltered homeless adults in Boston, Massachusetts, 2000–2009. *JAMA Intern Med*. 2018;178(9):1242–8.
- 17 Bauer LK, Brody JK, León C, Baggett TP. Characteristics of homeless adults who died of drug overdose: a retrospective record review. *J Health Care Poor Underserved*. 2016;27(2):846–59.
- 18 Fine DR, Dickens KA, Adams LD, De Las Nueces D, Weinstock K, Wright J, et al. Drug overdose mortality among people experiencing homelessness, 2003 to 2018. *JAMA Netw Open*. 2022;5(1):e2142676.
- 19 Cawley CL, Kanzaria HK, Kushel M, Raven MC, Zevin B. Mortality among people experiencing homelessness in San Francisco 2016–2018. *J Gen Intern Med*. 2022;37(4):990–1.
- 20 Hibbs JR, Benner L, Klugman L, Spencer R, Macchia I, Mellinger A, et al. Mortality in a cohort of homeless adults in Philadelphia. *N Engl J Med*. 1994;331(5):304–9.
- 21 Fine DR, Lewis E, Weinstock K, Wright J, Gaeta JM, Baggett TP. Office-based addiction treatment retention and mortality among people experiencing homelessness. *JAMA Netw Open*. 2021;4(3):e210477.
- 22 Kemp PA, Neale J, Robertson M. Homelessness among problem drug users: prevalence, risk factors, and trigger events. *Health Soc Care Community*. 2006;14(4):319–28.
- 23 Johnson G, Chamberlain C. Homelessness and substance abuse: which comes first? *Aust Soc Work*. 2008;61(4):342–56.
- 24 McVicar D, Moschion J, van Ours JC. From substance use to homelessness or vice versa? *Soc Sci Med*. 2015;136:137:89–98.
- 25 Ginzler JA, Cochran BN, Domenech-Rodríguez M, Cauce AM, Whitbeck LB. Sequential progression of substance use among homeless youth: an empirical investigation of the gateway theory. *Subst Use Misuse*. 2003;38(3-6):725–58.
- 26 DiGiuseppi GT, Prindle J, Rice ER, Davis JP. Longitudinal associations between homelessness and substance use: investigating demographic differences for young adults in treatment. *Subst Use Misuse*. 2023 Oct 27. [Epub ahead of print].
- 27 Cusack M, Montgomery AE. Examining the bidirectional association between veteran homelessness and incarceration within the context of permanent supportive housing. *Psychol Serv*. 2017;14(2):250–6.
- 28 To access the appendix, click on the Details tab of the article online.
- 29 Wong YLI, Park JM, Nemon H. Homeless service delivery in the context of continuum of care. *Adm Soc Work*. 2006;30(1):67–94.
- 30 Turnham J, Wilson E, Burt M. A guide to counting unsheltered homeless people [Internet]. Washington (DC): Department of Housing and Urban Development, Office of Community Planning and Development; 2004 Oct [cited 2023 Nov 30]. Available from: <https://www.hudexchange.info/sites/onecpd/assets/File/Guide-for-Counting-Unsheltered-Homeless-Persons.pdf>
- 31 Portman J, Stewart M. Every tenant's legal guide. 9th ed. Berkeley (CA): Nolo; 2018.
- 32 Stewart M, Warner R, Portman J. Every landlord's legal guide. 13th ed. Berkeley (CA): Nolo; 2016.
- 33 Oster E. Unobservable selection and coefficient stability: theory and evidence. *J Bus Econ Stat*. 2019;37(2):187–204.